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ABSTRACT:

Proton Exchange Membrane Fuel Cells (PEMFC) are available for a wide variety of applications such as transportation, micro-cogeneration or powering of portable devices. However, even if this technology becomes close to competitiveness, it still suffers from too short life duration to pretend to a large scale deployment. In a perspective of a longer lifetime, prognostics aims at tracking and anticipating degradation and failure, and thereby enables deciding mitigation actions to increase life duration. Yet, the complexity of degradation phenomena in PEMFC can make prognostic implementation really tough. Indeed, a PEMFC implies multiphysics and multiscale phenomena making the construction of a physics-based aging model very complex. Moreover, prognostics should also take into account external events influencing the aging. Among them, characterization techniques such as electrochemical impedance spectroscopies and polarization curves introduce disturbances in the stack behavior, and a voltage recovery is observed at the end of characterizations process. It means that irreversible degradation and reversible decrease of performances have to be considered. This work proposes to tackle this problem by setting a prognostics system that includes disturbances' effects. We propose a hybrid prognostics approach by combining the use of empirical models and available data. In an evolving system like a fuel stack, a particle filtering framework seems to be really appropriate for life prediction as it offers the possibility to compute models with time varying parameters and to update them all along the prognostics process. Moreover, it offers a great adaptability to include characterization effects and allows giving prediction with a quantified uncertainty. The logic of the work is the following. First, it is shown that simple empirical models only taking into account the aging are very limited in terms of prognostics performances. Then, some features describing the impact of characterization on the stack behavior and aging are extracted and a more complete prognostics model is built. Finally, the new prognostic framework is used to perform remaining useful life estimation and the whole proposition is illustrated with a long term experiment data set in constant current solicitation and stable operating conditions.

KEYWORDS: PEMFC, Prognostics, Remaining Useful life, Particle filter

1. Introduction

Proton Exchange Membrane Fuel Cells (PEMFCs) are getting closer and closer to worldwide commercialization. However, to ensure a wide spreading of this technology, some improvements are still needed mostly dealing with increasing the life duration. To achieve this goal, several possibilities are available such as: working on materials, improving the design or developing Prognostics and Health Management (PHM) for PEMFC. This is the solution chosen in this work.

PHM is a set of activities that allow following the state of health of the system throughout its entire life but also taking the right decisions at the right time to help extending the Remaining Useful Life (RUL) of that system. This is mainly achieved by prognostic which aims at tracking and anticipating degradation and failure, and thereby enables deciding mitigation strategies.

Following and modelling the degradation of a PEMFC stack is not an easy task. Indeed some characterization techniques used for monitoring the system, such as electrochemical impedance spectroscopies (EIS) and polarization curves introduce disturbances in the stack behavior. Power recoveries are observed after these characterization phases imposing to take into account reversible and irreversible degradations.

Consequently, this work aims at building a prognostics framework which models the effects of disturbances introduced during characterization phases. To do so, first PHM will be presented in Section 2 with a focus on prognostics. This section will also present a literature review on prognostics of PEMFC and introduce a previous work realized without modelling the disturbances to set some bases. Then, the approach chosen to describe the aging of the stack will be described and the data as well as the empirical models introduced in Section 3. This will lead to the description of the prognostics framework in Section 4. Then the approach will be illustrated by predicting the behavior and estimating the RUL of two PEMFC stacks working under constant current solicitation.

2. Overview of Prognostics and Health Management

2.1 Processing layers of PHM

The growing need of availability, safety or reliability is a major issue for all industrial systems. Maintenance is an efficient way to meet these requirements while reducing costs linked to the useful life of the system. Maintenance strategies evolve with the desired needs moving from breakdown maintenance to preventive maintenance and more recently to Condition-Based Maintenance (CBM). This change allows adopting a “predict to prevent” strategy instead of a “fail to fix” one making possible to anticipate the failures and maintain the correct part of the equipment at the right time by taking into account the current and future state of health of the system [1].
To do so, CBM employs real-time monitoring data to, first, estimate the state of health of the system, then diagnose and/or predict failures, to finally optimize the use of the system and the maintenance strategy. Indeed, a large set of activities are performed jointly ranging from data acquisition, data processing to decision making. This set of activities is known as Prognostics and Health Management (PHM) [2]. It is made of seven layers which main objective is to enhance the effective reliability, availability and performance of equipment by detecting current and approaching failures. Thereby, it allows protecting the integrity of the system and avoiding unanticipated operational problems that would lead to mission performance deficiencies, important degradations or adverse effects on mission safety.
As mentioned earlier, PHM is composed of seven layers forming a global architecture dedicated to three main actions: observing, analyzing and acting, as shown on Figure 1.

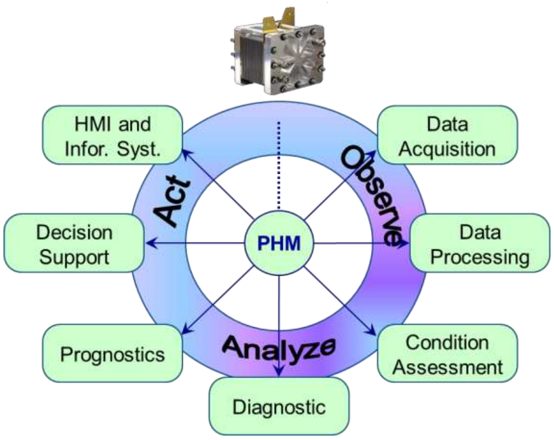

Figure 1. PHM Architecture with its seven layers

The layers are defined as follows.

- Layer 1 – Data acquisition

  It provides the PHM application with data coming from all the sensors and characterization means used on the system.

- Layer 2 – Data processing

  It receives data from layer 1 and performs signal transformations or features extraction, reduction and selection.

- Layer 3 – Condition assessment

  It determines the current state of health of the system by detecting and localizing faults. It compares on-line data with expected values of system’s parameters. It should also be able to generate alerts based on preset operational limits.

- Layer 4 – Diagnostic

  It determines if the condition of the system has degraded. The module also generates a diagnostic record and suggests fault possibilities. It allows isolating and identifying the component that has ceased to operate (past propagation from effects to causes).

- Layer 5 – Prognostics

  It predicts the future condition of the monitored system, subsystem or component. The module should be able to acquire data from all the previous modules (propagation from causes to effects).

- Layer 6 – Decision making

  It provides recommended maintenance actions or alternatives to run the system until the mission is completed (even in a degraded mode). This should be done automatically.

- Layer 7 – Human–Machine Interface (HMI)

  This module receives the data from all previous layers. It could be built into a regular human-machine interface.

It can be seen from these definitions that the prognostics layer is of great interest. Let's now describe more precisely this key process of PHM.

2.2 Focus on prognostics

Even if some divergences can be found in the literature, prognostics can be defined as proposed by the International Organization for Standardization: "prognostics is the estimation of time to failure and risk for one or more existing and future failure modes". With this definition, prognostics is also called "prediction of a system's lifetime". Indeed, it aims a predicting the Remaining Useful Life (RUL) before a failure occurs, given the current machine condition and solicitation, and its past and future operation profiles. Various approaches are available to perform prognostics divided into three main categories: model-based, data-driven and hybrid (mix of both previous ones). They won't be detailed here, for information the reader is invited to refer to [3-6]. Whatever the approach used, prognostics realization is divided into two phases: learning and prediction. During the learning phase, the prognostics tool learns the behavior of the system and uses the data available to adjust its model parameters. This phase lasts until the last data available is used and the date chosen to start the prediction is reached. This date will be called t_p. Then the prediction stage begins. The prognostics tool estimates the evolution of the system and predicts when a critical threshold before failure is going to be reached. Let's call that date $t_{failure.}$ The duration between $t_{failure}$ and t_p gives the RUL. This process is illustrated by Figure 2.

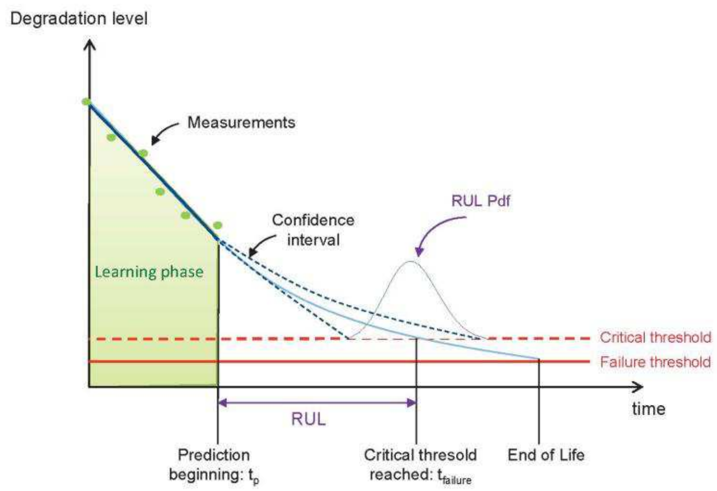

Figure 2. Representation of the prognostics process

It can be seen on Figure 2 that two thresholds are defined: a critical threshold and a failure threshold. This last one may indicate the end of life of the system. So, in order to have enough time to plan mitigation strategies, it is preferable to know when the system will reach a critical threshold slightly higher than the

failure one. It also protects the system in case of late predictions given by the prognostics (i.e. predicted RUL > actual RUL).
Finally, it can be noticed that the prognostics gives estimations with a confidence interval. This intends to face the problem of the uncertainty coming with the predictions, which is a major issue in prognostics applications [5, 7]. This uncertainty can come from the system, the way it used, the sensors or from the prognostics approach deployed. Consequently, the framework set for prognostics must take into account the uncertainty at all the process stages. This can be done, as illustrated on Figure 2, by giving a probability distribution of all the possible states of the system at one date instead of giving a single value. The estimated state evolution is given by taking the most probable state (maximum value of the distribution) taken from each distribution. At the end of the process, the RUL is given with a probability density function (pdf) and decision making has to be done accordingly to the associated uncertainty.

2.3 Prognostics of PEMFC

2.3.1 State of the art

Prognostics, and more generally PHM, is quite a recent topic regarding PEMFC. Indeed, a lot of research work regarding PEMFC has been and still be done, but adopting a PHM point of view to tackle the problem of reliability and life duration of the stack is quite new. As this part will only deal with a literature review regarding prognostics, the reader is invited to refer to [8] for more information about the state of the art of PHM of PEMFC.
Regarding prognostics, two kinds of works aim at providing RUL predictions. In [9], and in an extended version [10], the authors propose a model-based prognostics relying on an unscented Kalman filter to predict the degradation of a cell's electrochemical active surface area. The results are very interesting and show good performance according to the α-performance metrics described in [11]. However, this prognostics covers a short period of time (300 h) when thousands of hours are expected for a PEMFC lifetime. Moreover, it is performed on a single cell instead of a whole stack which can limit the scope of use of the results.
For its part, [12] proposes a hybrid prognostics model based on particle filtering to estimate the voltage drop during the aging of a 5-cell stack under constant load solicitation. Three empirical models are proposed and tested to predict the global trend of voltage evolution through time and then to estimate the RUL. This work shows promising results but the accuracy of the prediction is limited by the non-consideration in the models of the disturbances induced by characterization phases.

2.3.2 Limitations highlighted by the previous work

As stated above, not considering the disturbances introduced by Electrochemical Impedance Spectroscopy (EIS) and polarization curve measurements was one of the major limitations of our previous work. Indeed, after these characterizations, voltage recoveries can be observed modifying the behavior of the stack. The models presented in [12] are not able to catch these recoveries and this has a great impact on predictions mostly by introducing a wide uncertainty and dispersion of the results. However, this work allowed us to choose which empirical model can be used to represent the voltage drop during aging and set some bases for the work presented in the next parts.

3. Describing the aging of a PEMFC stack

3.1 Aging data

Two data sets will be used for prognostics illustrations and will be referred as S1 and S2. S1 comes from the aging of a 5-cell PEMFC stack run under a constant current load of 60A during approximately 1750 hours. S2 also comes from a 5-cell PEMFC stack, but that time under a constant current load of 70A during 1000 hours. This description emphasizes one main hypothesis and limitation of our prognostics framework: we consider stacks working in constant operating conditions and under constant load solicitation.
Both stacks went through the same kind of measurements during the aging:

- Load measurements (to compare with the imposed one);
- Voltage measurements;
- Polarization curves;
- EIS.

For our prognostics purpose, we chose to work with the stack power, so only voltage and current measurements are used in order to have the power loss of the stack through time. Polarization curves and EIS, following each other during the experiments, will be referred as "characterization phases" and only their impact on the observed power will be considered in this work. 12 characterizations phases were made for S1 whereas 8 where made for S2.

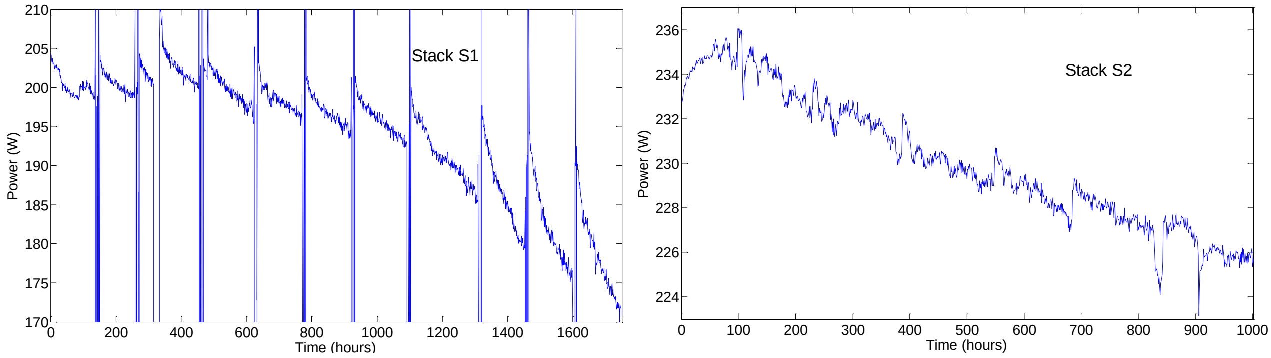

Figure 3. Power evolutions through the aging for stacks S1 and S2

3.2 Aging modeling

Before giving models expressions, few observations can be made thanks to the power signals of Figure 3. As the effects of characterization phases appear more clearly on S1, comments will be made from the left part of Figure 3, but also from Figure 4 that shows a zoom from S1.

By considering the power evolution, it can be seen that three stages seem to repeat all along the lifetime: a drop due to aging, then a characterization phase which is followed directly by a power recovery. The reason for these performance recoveries remains unclear. Yet, it can be assumed that returning to a nominal load demand after current variations made during characterizations impact the behavior. Indeed, it re-homogenizes the gas and liquid distributions within the stack and reset the operating conditions. Consequently, it would cancel some negative reversible effects. Based on that hypothesis, it can be assumed that the recovery observed is only limited by irreversible degradation occurring within the stack.

Then, by giving a closer look to the power evolutions between characterizations, it can be observed that the drops seem to accentuate, to occur faster and faster. This could be attributed to the degraded states of the different cells and their components that worsen and it should be taken into account when setting the aging models.

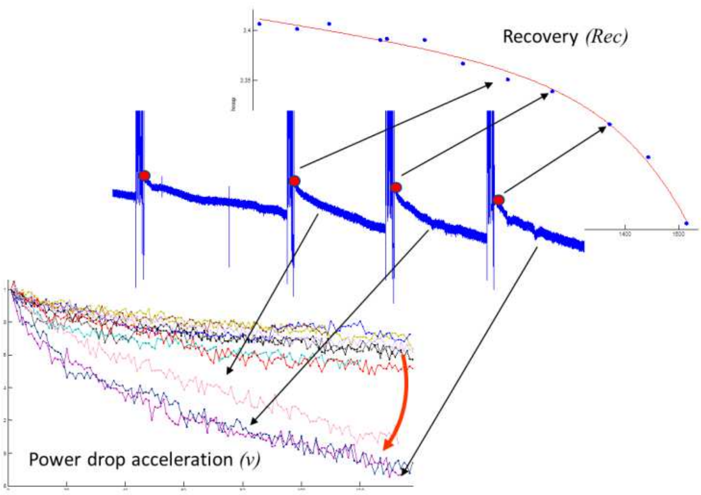

Figure 4. Power recovery (Rec) and drop acceleration (v)

To build our model, we formulate the hypothesis that as the operating conditions and loads were kept constant, all the aging observed is time-effects. This implies that our model just have to be time-dependent. To be as precise as possible, our modeling of aging contains three models:

- One for power degradation between characterizations;
- One for power drop acceleration;
- And finally, one for the recovery.

These models are now detailed.

3.2.1 Power degradation

This model aims at describing the power degradation in the nominal conditions. This model is composed by a linear part and a logarithmic one:

$$x(t) = a_1.ln(t) – v.t + c_1 \quad (1)$$

Where $x(t)$ represents the power, a_1 and c_1 coefficient to define and v a coefficient driving the speed of the power drop that will describe later. The logarithmic part allows describing a transient phase while the linear one represents the steady decay period. This expression is set based both on observations and on the comments of the authors in [] suggesting the presence of two functioning phases after characterization.

3.2.2 Drop acceleration

As clearly shown on Figure 4 and described earlier, the power decreases faster and faster when the stack ages. This means that the coefficient v in (1) evolves with time. By normalizing and comparing the different parts between characterizations (left-hand bottom of Figure 4), we were able to extract a global trend for v evolution. Calculating the quantity dx/dt a for certain number of points during the learning phase enables writing the following expression:

$$v(t) = -a_2.exp(b_2.t) + c_2 \quad (2)$$

With v the coefficient from the power degradation model, a_2, b_2 and c_2 coefficients to determine.

3.2.3 Recovery modeling

Finally, the last phenomenon to model is the power recovery. This recovery is represented by round dots on Figure 4. As previously mentioned, this recovery is limited by irreversible degradation occurring within the stack. As it still is very complicated to find a model of irreversible degradation suitable for prognostics, once again a global trend is extracted from our data sets. Thereby, the recovery follows:

$$Rec(t) = a_3.exp(b_3.t) + c_3.exp(d_3.t) \quad (3)$$

Where Rec is the recovery and a_3, b_3, c_3 and d_3 are coefficients to determine.

Equations (1-3) combined together enable catching the behavior of the stack during its aging. These equations have now to be integrated in a prognostics framework.

4. Prognostics in a particle filtering framework

To perform the predictions, a hybrid prognostics approach is set. Indeed, it enables combining our empirical models with the data available. Moreover, it can be noticed that our problem combines the different characteristics of a nonlinear Bayesian tracking problem [13, 14]: the models are non-exact, non-stationary, nonlinear and may contain non-Gaussian noise. To solve that problem, different tools are available but the particle filter solution was kept as it fits to our problem and shows good results in the applications available in the literature [15-17].

4.1 Nonlinear Bayesian tracking with particle filters

A Bayesian tracking problem is defined by two equations: a state model and an observation model [13,14]. The state model describes the evolution of a system state. That state, noted $\{x_k , k \in \mathbb{N}\}$, is going to evolving following:

$$x_k = f(x_{k-1}, \theta_k, \lambda_k) \quad (4)$$

where f is a transition function from one state to the next one, θ_k is a vector of unknown parameters in the model and λ_k is an independent identically distributed (i.i.d.) noise, if such noise exists in the model.
The tracking process recursively estimates x_k from the measurements introduced by the observation model $\{z_k , k \in \mathbb{N}\}$:

$$z_k = h(x_k, \mu_k) \quad (5)$$

with h the observation function and μ_k an i.i.d. noise.
The objective of the problem is to estimate recursively a probability distribution of the state at time k by constructing the probability density function (pdf) $p(x_k| z_{1:k})$. To start, it is assumed that the initial pdf $p(x_0| z_0) \equiv p(x_0)$ is available. $p(x_k| z_{1:k})$ can be obtained recursively repeating two stages: prediction and update. The analytical expressions of the stages can be found in [13]. They give the optimal solution to the problem.

Unfortunately, in most of cases these equations cannot be solved analytically. That's why, tools such as particle filter are used to give an approximate solution.
Particle filters are Monte Carlo-based tools relying on the Bayes theorem. The principle of particle filter for prognostics is quite simple. At the initial time, the initial distribution $p(x_0)$ is split into n samples, called particles. Then during the learning phase of prognostics, three steps are repeated until the end of the process:

- Prediction: particles are propagated from state $k-1$ to state k using the state model
- Update: a new measurement coming z_k allows calculate a likelihood function $p(z_k|x_k)$. This probability shows the agreement between the prediction and the measurement and allows attributing weight to each particle according to that likelihood. Particles with the higher weight should represent the most probable states.
- Re-sampling: to avoid a degeneracy of the filer, particles with the lower weights (a minimum weight is fixed) are eliminated and the ones with higher weights are duplicated to maintain a sufficient number of particles.

This process is illustrated on Figure 5 (a).
Then comes the prognostics prediction phase. As during this prediction phase (do not confuse with the prediction phase of the filter itself) no more data is available to perform the update and resampling stages, the particles are only propagated by the state model until the failure threshold is reached.

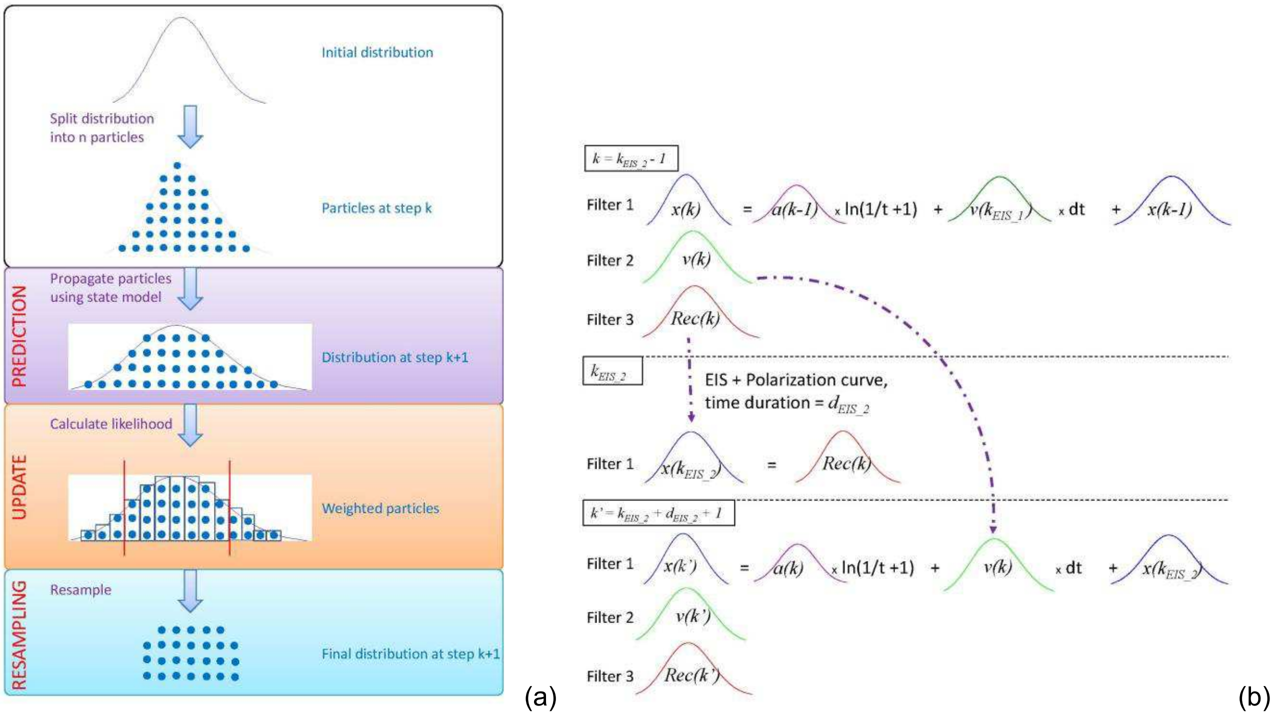

Figure 5. (a) Principle of particle filter – (b) Interaction between the different models

4.2 Adaptation to the PEMFC case

To set our prognostics framework, as three models are built, three particle filters work in parallel. Filter 1 estimates the power aging, Filter 2 estimates the coefficient v and Filter 3 estimates the recovery. Three filters means three states equations obtained by transforming recursively (1-3):

$$x_k = -a_1.ln(1/k+1) + v.d\tau + x_{k-1} \quad (6)$$
$$v_k = -a_2.exp(b_2.k.d\tau).(1 - exp(-b_2)) + v_{k-1} \quad (7)$$
$$Rec_k = a_3.exp(b_3.k.d\tau).(1 - exp(-b_3)) + c_3.exp(d_3.k.d\tau).(1 - exp(-d_3)) + Rec_{k-1} \quad (8)$$

With $d\tau$ the time step between two measurements (1 hours in this case).
As they are working in parallel, they are synchronized on the same time step. So, when the date of a characterization is detected thanks to a planning integrated in the framework, it implies that a power recovery occurs. Consequently, particles from Filter 3 are used to update the power aging. The last distribution estimated by Filter 3 is used as the next distribution in Filter 1, see Figure 5 (b). A characterization also marks the beginning of a faster voltage drop, so the particles estimated for v by Filter 2 are used to replace the old v, only valid before the last characterization, in Filter 1. Let's now see the performance of this framework.

5. Experiments and discussion

To perform prognostics, failure thresholds have to be defined. As no dramatic failure occurred during the experiments, the ends of life thresholds are defined by the last data available for each stack.

5.1 Power behavior predictions

Before estimating the RUL, the power degradation has to be predicted. Considering the number of unknown parameters in the three state equations, at least four characterizations data are needed to estimate the initial parameter distributions and thereby initialize the filters. In practice, it means that the minimum for the learning is 500 hours for S1 and 400 hours for S2. Figure 6 shows an example of power prediction or S1 with a training using 800 hours of the data set. It can be noticed that before 1100 hours, the prognostics framework catches pretty well the behavior of power during aging. However, it seems that the logarithmic part of the power drop is rapidly completely ignored by the estimations. Maybe its coefficient should vary with an equation as the coefficient v. After 1100 hours, the recovery function slightly over-estimates the recovery values with the error increasing with time. This observation was also made on the results from S2. The recovery function should be adjusted to better follow the recovery trend after the half of the stack life.
Regarding the power drop speed, the slope seems to be close to the reality but as the logarithmic part is hidden by the linear one, the error existing between the prediction and the data can reach 10 W as it can be seen around 1400 hours. This error between real data and predictions is less important with S2 as the slope decreases slower during the 1000 hours of the experiment. But it could have appeared if data older than 1000 hours were available.
These results show that the models become to be closer to the reality than in the first application [12], but they still have to be improved. Let's now analyze and comment the RUL estimates with the α-metrics described in [11].

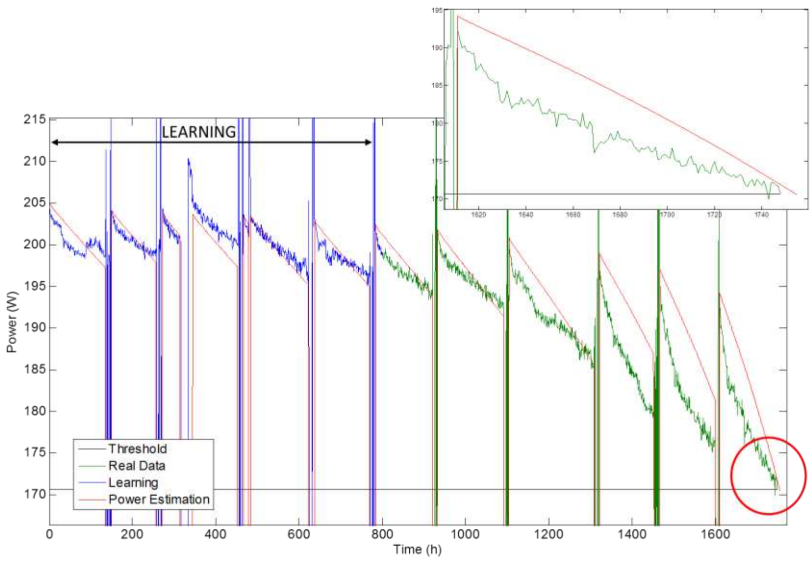

Figure 6. Power prediction compared to the real one for a learning phase of 800 h on S1

5.2 RUL estimates

5.2.1 Stack S1: first estimations

First it is necessary to precise, that all the predictions were run 100 times to estimates the uncertainty introduced by the prognostics framework. So, for fixed initial distributions, a fixed threshold and a chosen learning length the framework was launched and we obtained that our 100 predictions are normally distributed and the range of the distribution is 20 hours. To be sure that this is result is not specific of a learning length, this process was repeated for all the learning lengths used to evaluate the RUL evolution. And the result was always the same. It also enable concluding that our framework gives predictions with an uncertainty of ± 10 hours. Knowing that, we can now evaluate our RUL estimates.

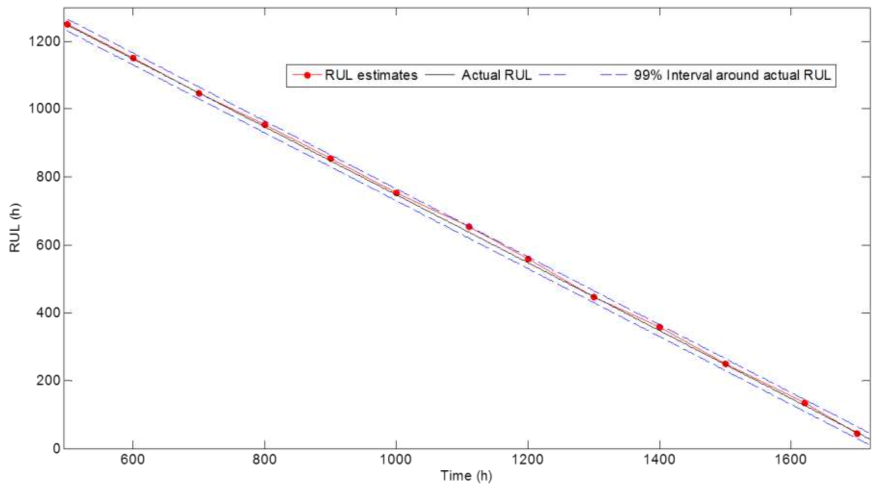

Figure 7. RUL evolution throught time for S1

Regarding S1, even if the power estimation is imperfect, the RUL estimates are quite convincing (Figure 7). The predictions are all contained at ± 17.48 hours of the actual RUL. By adding the uncertainty estimated above, the RUL estimates for S1 are precised at ± 27.48 hours. This makes a maximum error of 1.7% on 1750 hours.

5.2.2 Stack S2: comparison with and without disturbances inclusion

As results from previous prognostics experiments were available for S2, it is interesting to compare the new RUL estimates with the old ones from [12]. Both series of results are represented on Figure 8, RUL estimated with a model not taking into account characterization disturbances are shown in red whereas the ones obtained with the new model are represented in black. By just considering that figure, the accuracy improvement is not striking. Indeed, it can be seen that the new RUL estimates are a little closer to the reality and gives less late predictions. But the major improvement concerns the uncertainty coming with prediction. In our previous paper, the RUL estimates were given with an accuracy of ± 90 hours and an associated uncertainty of more than 200 hours. By taking into account the recovery and degradation acceleration phenomena the accuracy is limited at ± 40 hours around the actual RUL value and the uncertainty, as mentioned above, is reduced at ± 10 hours. That's clearly show the more phenomena are taken into account the most our framework becomes precise, with a maximum error of 5% on 1000 hours.

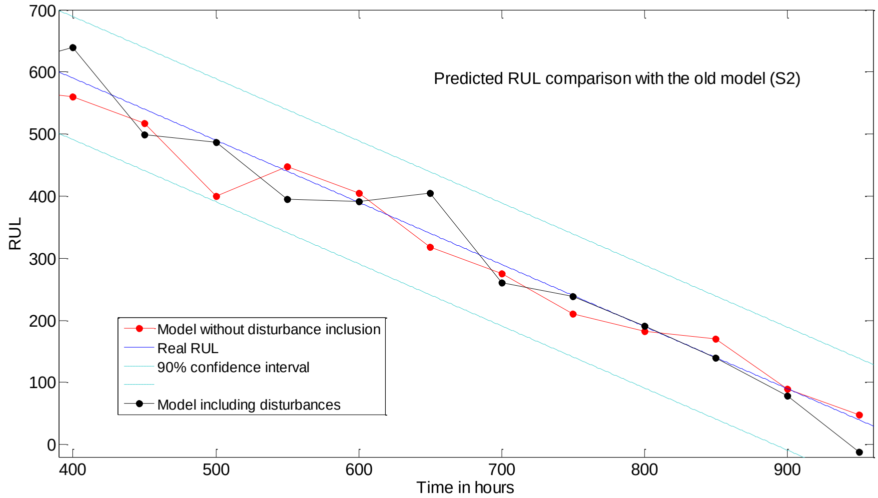

Figure 8. RUL evolution throught time for S2

5.3 Discussion

It can be noticed that the prognostics framework seems to offer more accurate results with S1 than with S2. Different reasons may explain that. First, it can be explained by the threshold chosen for prediction. Indeed, by looking at Figure 6, it can be observed that the power estimation luckily meets the failure threshold at the right place. But if the threshold was higher, the prediction would not be so good. Another explanation may come from the use of the particle filters. As previously explained, one has to give the initial distribution for state $p(x_0)$ but also for the parameters of the state model. $p(x_0)$ is defined manually each time we change the data set but no formal procedure has been selected yet. So if these initial distributions are not precise enough, it can impact the predictions.

6. Conclusion

This work intend to present a new prognostics framework able to predict the power evolution and estimates the remaining useful life of a PEMFC stack which behavior is modified by characterization phases. The framework combines three particles filters estimating the power aging, but the recoveries and the power drop accelerations observed after characterizations. This allows giving better prognostics results that a simple global trend model. Even if the behavior predictions are not perfect, they show that the empirical models used are not so far from reality and should give very good results with some improvements. Moreover the framework is able to give RUL estimates with an error less than 30 hours in the best case and less than 50 hours in the other one. Considering the lifetimes of 1750 and 1000 hours of the stack, these results are quite convincing. A next step of that work is to build physic-based models, to justify the empirical ones and to improve the accuracy. Another extension will be including variable operating conditions which would better represent the real use of a PEMFC stack.

Acknowledgement
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References
[1] Lebold M, Thurston M. “Open standards for condition-based maintenance and prognostic systems”, 5th Annual maintenance and reliability conference 2001.
[2] Pecht M. “Prognostics and health management of electronics”, Wiley Online Library, 2008.
[3] Heng A, Zhang S, Tan AC, Mathew J. “Rotating machinery prognostics: state of the art, challenges and opportunities” Mech Syst Sig Process, 23, 724-39, 2009
[4] Jardine A-K-S, Lin D, Banjevic D. “A review on machinery diagnostics and prognostics implementing condition-based maintenance”, Mech Syst Sig Process, 20, 1483-510, 2006
[5] Vachtsevanos G, Lewis FL, Roeme M, Hess A, Wug B. “Intelligent fault diagnostic and prognosis for engineering systems”, John Wiley & Sons 2006
[6] Sikorska J, Hodkiewicz M, Ma L. “Prognostic modelling options for remaining useful life estimation by industry”, Mech Syst Sig Process, 25,1803-36, 2011
[7] Saxena A, Celaya J, Saha B, Saha S, Goebel K. “Metrics for offline evaluation of prognostic performance”, Int J Progn Health Manag, 1, 20, 2010
[8] M. Jouin, R. Gouriveau, D. Hissel, M-C. Péra, and N. Zerhouni, “Prognostics and health management of PEMFC state of the art and remaining challenges,” International Journal of Hydrogen Energy, vol. 38, no. 35, 15 307 – 15 317, 2013
[9] X. Zhang and P. Pisu, “An unscented kalman filter based approach for the health-monitoring and prognostics of a polymer electrolyte membrane fuel cell,” Proceedings of the annual conference of the prognostics and health management society, 2012.
[10] Zhang, X., & Pisu, P. “Prognostic-oriented Fuel Cell Catalyst Aging Modeling and Its Application to Health-Monitoring and Prognostics of a PEM Fuel Cell”, IJPHM, vol 5, Page 16, 2014
[11] A. Saxena, J. Celaya, B. Saha, S. Saha, and K. Goebel, “On applying the prognostic performance metrics,” in Proceedings of the annual conference of the prognostics and health management society, 2009
[12] M. Jouin, R. Gouriveau, D. Hissel, M-C. Péra, and N. Zerhouni, “Prognostics of PEM fuel cell in a particle filtering framework,” International Journal of Hydrogen Energy, vol. 39, no. 1, pp. 481 – 494, 2014.
[13] A. Doucet, N. de Freitas, N. Gordon, and A. Smith, “Sequential Monte Carlo Methods in Practice”, ser. Information Science and Statistics. Springer, 2010.
[14] M. S. Arulampalam, S. Maskell, N. Gordon, and T. Clapp, “A tutorial on particle filters for online nonlinear/non-gaussian bayesian tracking,” Signal Processing, IEEE Transactions on, vol. 50, no. 2, pp. 174–188, 2002.
[15] D. An, J-H. Choi, N.H. Kim, “Prognostics 101: A tutorial for particle filter-based prognostics algorithm using Matlab”, Reliability Engineering & System Safety, Vol 115, 161-169, 2013
[16] K. Goebel, B. Saha, A. Saxena, J. Celaya, and J. Christophersen, “Prognostics in battery health management,” Instrumentation Measurement Magazine, IEEE, vol. 11, no. 4, pp. 33–40, 2008.
[17] Y. Xing, E. W. Ma, K.-L. Tsui, and M. Pecht, “An ensemble model for predicting the remaining useful performance of lithium-ion batteries,” Microelectronics Reliability, vol. 53, no. 6, pp. 811 – 820, 2013